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A New Approach for Segmentation of Fused Images using Cluster based Thresholding

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***Abstract*—This paper proposes the new segmentation technique with cluster based method. In this, the multi source medical images like MRI (Magnetic Resonance Imaging), CT (computed tomography) & PET (positron emission tomography) are fused and then segmented using cluster based thresholding approach. The edge details of an image have become an essential technique in clinical and research-oriented applications. The more edge details of the fused image have obtainable with this method. The objective of the clustering process is to partition a fused image coefficients into a number of clusters having similar features. These features are useful to generate the threshold value for further segmentation of fused image. Finally the segmented output is compared with standard FCM method and modified Otsu method. Experimental results have shown that the proposed cluster based thresholding method is able to effectively extract important edge details of fused image.**

***Index Terms*—Discrete Wavelet transforms; General Fusion Process; Clustering Process; Threshold estimation.**

I. Introduction

Image segmentation is a process of partitioning an image into some non-overlapping meaningful homogeneous regions. Image segmentation is having many applications, such as image retrieval, geographical imaging, target tracking and medical imaging. The final objective of segmentation process is to separate an image into distinct regions with respect to some characteristics such as gray value, texture or statistical behavior [Ref.1]. The fully automatic brain tissue classification of medical images is of great importance for research and clinical study [Ref.14].

The implementation of feature extraction techniques are mostly important for pattern recognition and image processing problems [Ref.9]. The extracted features by feature selection method can effectively classify patterns. For this the two-dimensional DWT proposed by Mallat has been applied extensively for feature extraction of image processing applications due to its excellent properties of time frequency localization and adaptive multi-scale decomposition [Ref.2, Ref.3].

In [Ref.4] developed a new-cluster based feature extraction method for signals based on one-dimensional DWT, hence here this is effectively applied on images to acquire effective segmentation of fused images [Ref.13].

The medical images like MRI and CT provides high-resolution images with structural and anatomical information. PET images provide functional information with low spatial resolution. In the recent years, the success of MRI-CT [Ref. 7], PET-MRI [Ref. 5] & PET-CT [Ref.6] imaging in the clinical field triggered considerable interest in noninvasive functional and anatomical imaging. The limited spatial resolution in PET images is often resulted unsatisfactory in morphological analysis. Combining anatomical and functional tomography datasets provide much more qualitative detection and quantitative determination in this area [Ref.8].

In this paper proposes a new-clustering scheme that divides the 2-D DWT coefficients into clusters at each scale. The energy of each these clusters is treated as a feature that contains a useful piece of information about the image. Then the threshold value is extracted from these feature vectors to segment the fused image accurately.

The rest of the paper is organized as follows: Section 2 explains 2-D Discrete Wavelet Transforms. Section 3 presents generic fusion model. Section 4 explains the proposed segmentation method. Section 5 explains the overall proposed method. Section 6 the discussion on the experimental results. In the laconic section, the paper is concluded.

II. Discrete Wavelet Transform

Discrete Wavelet transform (DWT) provides a framework in which a signal is decomposed, with each level corresponding to lower frequency sub band, and higher frequency sub bands. There are two main groups of transforms: continuous and discrete. In one dimension the idea of the wavelet transform is to present the signal as a superposition of wavelets. If a signal is represented by f (t), the wavelet decomposition is

$$f(t) = \sum_{m,n} c_{m,n} \psi_{m,n}(t) \tag{2.1}$$

Where $\psi_{m,n}(t) = 2^{-m/2}\psi\left(2^{-m}t - n\right)$, m and n are integers. There exist very special choices of ψ such that $\psi_{m,n}(t)$ constitutes an ortho normal basis, so that the wavelet transform coefficient can be obtained by an inner calculation:

$$c_{m,n} = \langle f, \psi_{m,n} \rangle = \int \psi_{m,n}(t) f(t) dt \tag{2.2}$$

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In order to develop a multiresolution analysis, a scaling function ϕ is needed, together with the dilated and translated parameters of $\phi_{m,n}(t) = 2^{-m/2}\phi\left(2^{-m}t - n\right)$. The signal $f(t)$ can be decomposed in its coarse part and details of various sizes by projecting it onto the corresponding spaces. Therefore, the approximation coefficients $a_{m,n}$ of the function f at resolution 2^m and wavelet coefficients $c_{m,n}$ can be obtained:

$$a_{m,n} = \sum_k h_{2n-k} a_{m-1,k} \tag{2.3}$$

$$c_{m,n} = \sum_k g_{2n-k} a_{m-1,k} \tag{2.4}$$

Where h_n is a low pass FIR filter and g_n is a high pass FIR filter. To reconstruct the original signal, the analysis filter can be selected from a biorthogonal set which have a related set of synthesis filters. These synthesis filters $\tilde{h}$ and $\tilde{g}$ can be used to perfectly reconstruct the signal using the reconstruction formula

$$a_{m-1,l}(f) = \sum_n \left[\tilde{h}_{2n-l} a_{m,n}(f) + \tilde{g}_{2n-l} c_{m,n}(f)\right] \tag{2.5}$$

Equations (2.3) and (2.4) are implemented by filtering and down sampling. Conversely equation (2.5) is implemented by an initial up sampling and a subsequent filtering.

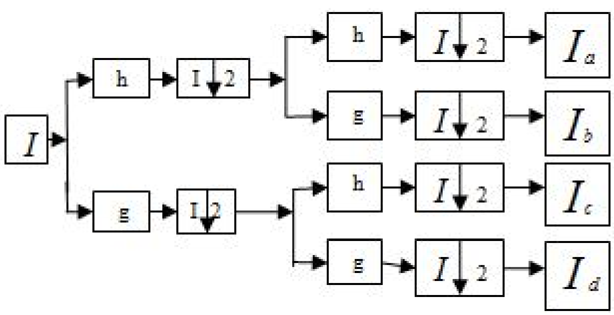

Fig 1: Structure of 2-D DWT

In a 2-D DWT, a 1-D DWT is first performed on the rows and then columns of the data by separately filtering and down sampling. This result in one set of approximation coefficients I_a and three set of detail coefficients, as shown in Fig 1, where I_b, I_c, I_d represent the horizontal, vertical and diagonal directions of the image I, respectively. In the filter theory, these four sub images correspond to the outputs of low-low (**LL**), low-high (**LH**), high-low (**HL**), and high-high (**HH**) bands. By recursively applying the same scheme to the LL sub band multi resolution decomposition with a desire level can then be achieved. There, a DWT with K decomposition levels will have M=3*K+1 such frequency bands. Fig 2 shows the 2-D structures of the wavelet transform with two decomposition levels. It should be noted that for a transform with K levels of decomposition, there is always only one low frequency band, the rest of bands are high frequency bands in a given decomposition level [Ref.11].

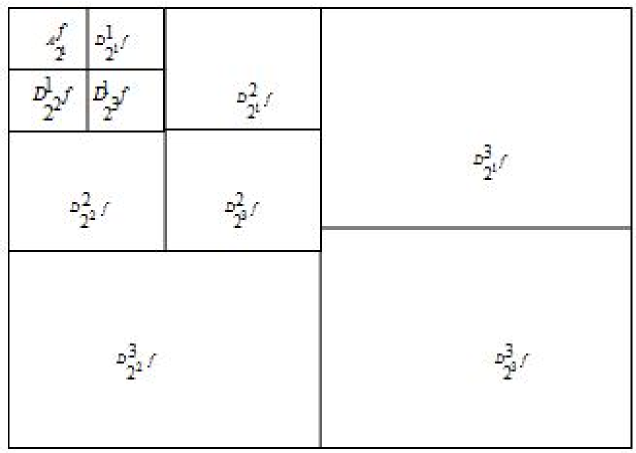

Fig: 2-D Discrete Wavelet Transform

III. Generic Model Of Multiscale-Based Image Fusion

In this paper, there are two different input medical source images A and B (like MRI & CT, MRI & PET, CT & PET). The image fusion algorithm should preserve all the salient features of source images. Fig 3 illustrates the generic image fusion frame work based on Multiscale image decomposition methods. The source images are firstly decomposed into low-frequency sub bands and a sequence of high-frequency sub

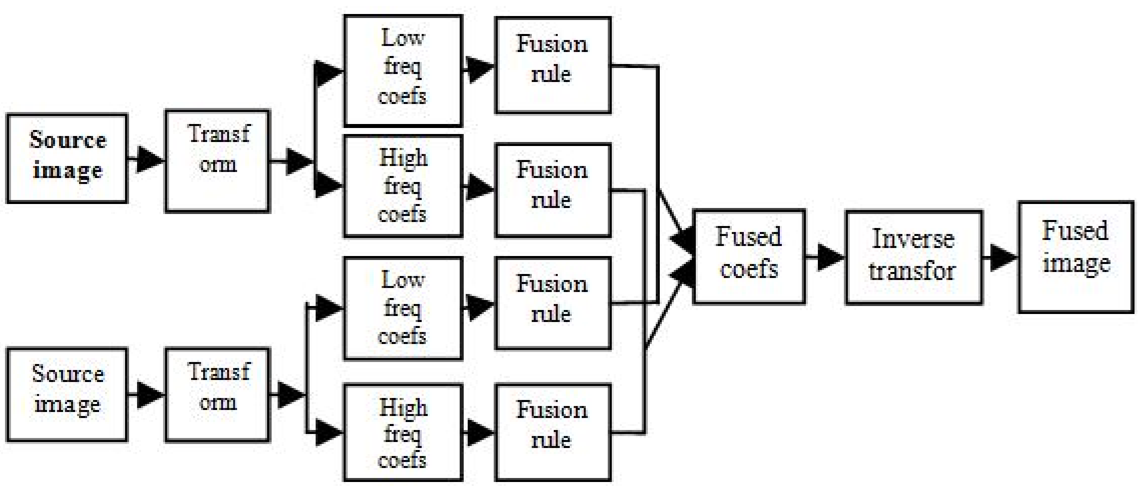

Fig 3: Block diagram of generic model of multi scale image fusion

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bands in different scales and orientations. Then the fusion coefficients are obtained from sub bands according to fusion rules. Finally, fused image is reconstructed by applying inverse transform on the fused sub bands.

The key issue in spatial domain algorithms is identifying the most important information in source images and fusing the salient information into the fused image [Ref.10].

IV. Proposed Segmentation Method With Threshold Estimation

After 2-D wavelet coefficients are obtained then the segmentation starts with cluster determination, cluster formation and threshold estimation methods. The following section explains these methods.

A. Clustering process

In generally, clustering is the process of partitioning a set of pixels into subsets called clusters having similar features. The choice of similarity criterion plays a significant role in the accuracy of the segmentation results. The term clustering refers to a number of different methods in this the pixels or coefficients are grouped into clusters in an unsupervised mode.

B. Cluster Determination

In this section, an improved clustering method for extracting features from the 2-D wavelet coefficients of the fused image. To determine the clusters, the 2-D discrete wavelet transform is computed for fused image. As per Fig 2, the image coefficients are represented and denoted by $\{A_{2^l} f, D^1_{2^j} f, D^2_{2^j} f, D^3_{2^j} f, 1 \le j \le J\}$. According to the central limit theorem the $G^p_{2^j} f$ for fused image with the mean and standard deviation of the image denoted by $\mu(A)$ and $\sigma(A)$ respectively.

$$G^p_{2^j} := \frac{1}{\sigma\left(SD^p_{2^j} f\right)}\left(SD^p_{2^j} f - \mu\left(SD^p_{2^j} f\right)\right)$$

$$P=1, 2, 3 \;\&\; j=1, 2, \text{——} J. \qquad (4.1)$$

Now apply the pittner and kamarhti [Ref.4] threshold of the form $T_{2^j} := \sqrt{2\left(\ln L_{2^j} - \ln \gamma\right)}$ with $\gamma \ge e^2$ to the elements of the matrix $G^p_{2^j} f$. In this L^j_2 being the number of computed detail coefficients at each scale. Finally the corresponding binary matrix $B^p_{2^j}$ with heavy side function: $\theta(x)=1$ for $x \ge 0$ and $\theta(x)=0$ for $x<0$.

$$B^p_{2^j} := \left(\theta\left(G^p_{2^j} - T_{2^j}\right)\right) \qquad (4.2)$$

C. Cluster formation

After computing the binary matrix $B^p_{2^j}$ from the fused wavelet coefficients, the grouping of clusters is formed with the neighboring pixel relation. The procedure is as follows:

- Assign a cluster number to the every value of '1' in the binary matrix. Each number act as seed point of that cluster.
- Grow the each cluster by starting with cluster seed point in the direction of 4- neighbors, only if neighboring value is 0. Otherwise no expansion is carried out if the neighbor is at boundary or value is 1.
- Repeat the previous step until no 0's remains in the matrix.
- The procedure illustrated in Fig 4. In Fig 4 (a) is the binary matrix and (b) cluster matrix with cluster formation process. In this example, 12 ones are existed in the binary matrix and then entire matrix forms 12 clusters with this process [Ref.3].

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

(a)

$$\begin{bmatrix} 1 & 2 & 3 & 3 & 3 & 3 & 3 & 3 \\ 4 & 5 & 6 & 3 & 3 & 3 & 7 & 3 \\ 8 & 9 & 10 & 3 & 3 & 3 & 7 & 3 \\ 8 & 9 & 10 & 11 & 3 & 3 & 7 & 3 \\ 8 & 9 & 10 & 11 & 3 & 3 & 7 & 3 \\ 8 & 9 & 10 & 12 & 3 & 3 & 7 & 3 \\ 8 & 9 & 10 & 12 & 3 & 3 & 7 & 3 \\ 8 & 9 & 10 & 12 & 3 & 3 & 7 & 3 \end{bmatrix}$$

(b)

Fig 4: (a) Threshold Matrix (b) Cluster Matrix

D. Threshold Estimation- Based on cluster features

From the procedure described in the previous subsection, the clusters 1, 2, 3—— etc are exited for the threshold image. Using these clusters the feature of each cluster is determined by,

$$U_i = \sqrt{\sum_{v \in U_i} v^2} \qquad (4.3)$$

Each feature of the cluster is determined by using above equation on fused wavelet coefficients. By using these feature values of all clusters, the threshold value is obtained by using the following equation:

$$Th = \max\left(U_i\right)/2^k \qquad k=1, 2\text{——}L\text{-}1 \qquad (4.4)$$

In this U_i is determined by above equation (4.3) for each cluster 'i'.

V. Overview Of The Proposed Method For Automatic Segmentation

The complete procedure from the determination threshold value to the automatic segmentation process is as follows:

Step-A: The input images (like MRI-CT or PET-CT or CT-PET) are decomposed by wavelet transform, forming J- level hierarchical structure.

Step- B: These wavelet coefficients are fused with simple

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additive process on each respective subband coefficients.

Step- C: Apply equation (4.1-4.4) on fused image to determine the clusters of the image according to Pitter and Kamarthi Lemma 1 conditions.

Step-D: The cluster formation process follows the cluster determination process to obtain final clustered image with N number of clusters.

Step-E: Use the threshold estimation algorithm for different values of k, to obtain final automatic segmented output of fused image.

The flowchart of the proposed method is shown in fig (5).

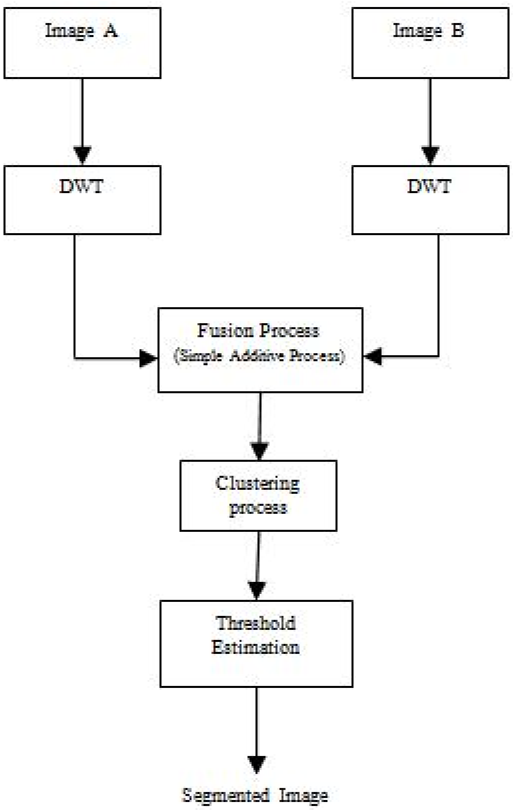
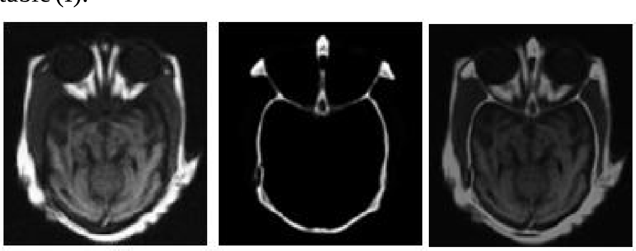


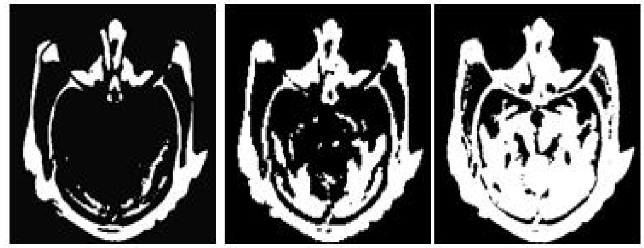
Fig 5: Flow chart of proposed method

VI. Experimental Results

In order to evaluate the effectiveness of the proposed algorithm, the segmented outputs are compared with Fuzzy Clustering method and modified otsu method proposed in [15] on medical images. The images are downloaded from [http://www.med.harvard.edu/AANLIB/home.html]. The results are shown in Fig (6-8). The number of clusters formed in each fused image type and threshold value is tabulated in table (I).



(a) (b) (c)



(d) (e) (f)

Fig 6: MRI-CT fusion results (a) Source image A (MRI) (b) Source image (CT) (c) Fused image. Segmented Image: (d) FCM Method (e) Modified Otsu method [Ref.15] (f) Proposed method with k=6

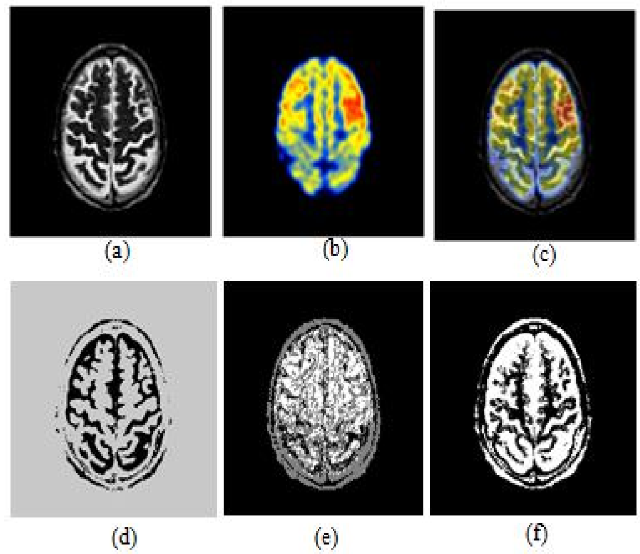


Fig 7: MRI-PET fusion results (a) Source image A (MRI) (b) Source image B (PET) (c) Fused image. Segmented Image: (d) FCM Method (e) Modified Otsu method [Ref.15] (f) Proposed method with k=5

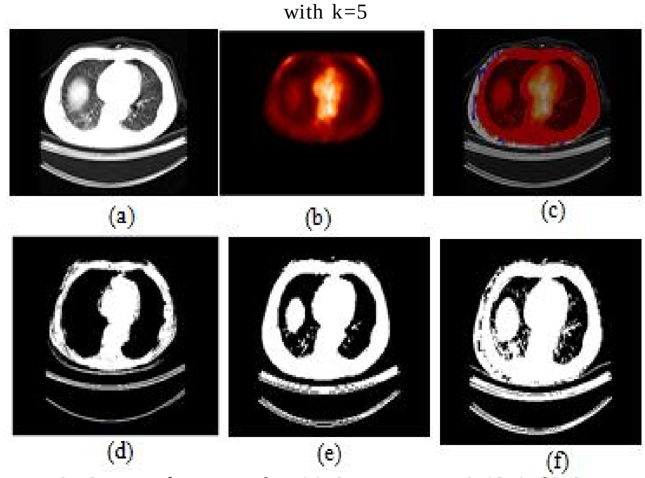


Fig 8: CT-PET fusion results: (a) Source image A (CT) (b) Source image (PET) (c) Fused image. Segmented Image: (d) FCM Method (e) Modified Otsu method [Ref.15] (f) Proposed method with k=0

Table I: Different Parameters of Proposed Method

Type of fused image	No. of clusters	Threshold value	K value
MRI-CT	3336	47.74	6
MRI-PET	3721	0.2468	5
CT-PET	3915	76.2	0

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Conclusions

In this paper, automatic image segmentation aided with threshold estimation scheme based on cluster features on medical images is presented. Firstly the simple additive fusion process is applied on respective wavelet sub band coefficients of different multi source images (like MRI-CT or PET-CT or CT-PET). Later the fused image was decomposed into J=3 levels by wavelet transform. The clusters are formed using cluster determination and cluster formation process. Finally the threshold value from cluster features used to segment the fused image. The resultant segmented image is compared with standard FCM method [Ref.12] and modified Otsu method. The threshold values and number of clusters are formulated in a tabular form. Experimental results show that the effectiveness of the edge segmented output for multisource images providing more edges of the fused image. This shows that the proposed method has the advantages of automation, no re-initialization of cluster centers, threshold value and also reducing the number iterations. The total number of clusters also resembles the content of more information in segmented output image. This proposed method can be extended with different multi scale transforms.

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